The Effect of Population Aging on Economic Growth, the Labor Force and Productivity

Nicole Maestas
Harvard University and NBER

Kathleen J. Mullen
RAND

David Powell
RAND

May 2017

Abstract

Population aging is widely expected to have detrimental effects on economic growth yet there is little empirical evidence about the magnitude of its effects. Many U.S. states have experienced substantial growth in the size of their older population during the last several decades. We use the predictable component of this growth, which varies substantially across states, to estimate the impact of population aging on per capita output. We find that a 10% increase in the fraction of the population ages 60+ decreases per capita GDP by 5.5%. Two-thirds of the reduction is due to slower growth in labor productivity across the age distribution, while one-third arises from slower labor force growth.

JEL Codes: J11, J14, J23, J26, O47

Keywords: population aging, GDP growth, demographic transitions

We are grateful to the Alfred P. Sloan Foundation Working Longer Program for grant funding. We thank David Cutler, Mary Daly, Edward Glaeser, Claudia Goldin, Larry Katz, Jim Poterba, Dan Wilson, Robert Willis and the CBO Panel of Economic Advisers for valuable feedback, as well as participants of the 2014 SIEPR/Sloan Working Longer Conference at Stanford University and the Harvard Labor Economics Seminar for their many helpful comments.

The fraction of the United States population ages 60 and older will grow by 21% between 2010 and 2020, and by 39% between 2010 and 2050 (Administration on Aging, 2014). This rapid aging of the U.S. population—itself the effect of historic declines in birth rates and death rates—is expected to slow economic growth, place considerable strain on government entitlement programs, and possibly lower per-capita consumption. While several studies have sought to forecast the future magnitude and timing of these economic effects (e.g., Cutler et al., 1990; Börsch-Supan, 2003; Vogel, Ludwig, and Börsch-Supan, 2013; National Research Council, 2012; Sheiner, 2014), there are few empirical estimates of the *realized* effect of aging on economic growth. This is a significant gap in knowledge. While demographic change is relatively easy to forecast because of its predetermined nature, the ensuing economic adjustments—by firms, individuals, and policymakers—are not similarly deterministic. It is thus difficult to forecast the path of economic growth without knowledge of the economic adjustments that may dampen or amplify the effects of demographic change. It is similarly difficult to gauge the amount and type of policy intervention that would counteract the economic and fiscal effects of population aging.

This paper presents the first empirical estimates of the realized effects of population aging on U.S. economic performance since 1980. Our analysis begins with the observation that population aging has been playing out over recent decades with varying degrees of intensity in different regions of the country. For example, between 1980 and 2010, the growth rate in the population ages 60+ was greater than 30% in six states (similar to the national rate of aging expected between 2010 and 2040) while during the same period, three states experienced *reductions* in the fraction of their population 60+. Some of this observed variation across states was predetermined many years prior by variation in birth rates that shaped the relative sizes of different cohorts far into the future. We use this predetermined variation as an instrumental variable for the realized aging experienced by a state at a future point in time in order to estimate the causal effect of population aging on the rate of growth in state Gross Domestic Product (GDP) per capita, the state labor force participation rate, and measures of labor productivity. The identifying assumption of our instrumental variables estimator is that a state's past age structure affects future economic outcomes only to the extent it predicts a state's future age structure, and not through any other channel. Under this exclusion restriction, the estimator incorporates the effects of all downstream economic responses to *predictable* population aging—including induced migration and changes in industry composition—while netting out confounding variation from unobserved factors that simultaneously affect economic growth *and* change the state age structure, such as trade shocks or changing tax incentives that might encourage firm mobility and differential net migration of older versus younger workers.

Our estimates imply that 10% growth in the fraction of the population ages 60 and older decreases growth in GDP per capita by 5.5%. Decomposing GDP per capita into its constituent parts—GDP per worker and the employment-to-population ratio—we find that two-thirds of the reduction in GDP growth is driven by a reduction in the rate of growth of GDP per worker, or labor productivity, while only one-third is due to slowing labor force growth. This finding runs counter to predictions that population aging will affect economic growth primarily through its impact on labor force participation, with little effect on average productivity (National Research Council, 2012; Burtless, 2013). Our productivity estimates are especially relevant as labor productivity in the United States has reached historical lows in recent years (see Fernald, 2016 for a discussion).

In addition, we find that the decline in productivity growth does not only reflect changes in the age composition of the pool of workers (who are on average older in states that age faster). Instead, evidence that population aging slows earnings growth across the age distribution suggests that it leads to declines in the average productivity of workers in *all* age groups, including younger workers. Importantly, these spillover effects do not appear to be driven by selection on the extensive labor supply margin, as we find population aging does not affect the employment rate of younger workers.

We test the sensitivity of our estimates to many factors. Our specification is derived formally and has precedence in the literature, but we also provide estimates based on other functional forms and find no meaningful differences in the estimates. We also find no evidence that states predicted to age at faster rates were on different growth paths such that underlying trends or mean reversion can explain our results. The estimates are robust to accounting for initial economic conditions or using different historical lags of the age structure—10, 20, 30, and 40 years—to predict the rate of future population aging, which strongly indicates that population aging is the causal channel and not underlying trends created by a particular initial age structure that occurred at a particular time.

Our approach yields an elasticity of economic growth with respect to population aging that incorporates the economic response to demographic changes, and which thus may be useful to predict future impacts on economic growth as population aging continues to unfold. An advantage of examining variation across economic units *within* the same country is we can hold constant the effects of national pension systems, labor market institutions and cultural retirement norms that may interact with population aging in cross-country studies. Our estimates should therefore be interpreted as the relationship between population aging and economic growth holding the national policy environment constant. Consequently, our research design does not capture "indirect" effects of population aging on the federal budget (e.g., rising Medicare expenditures) or the effects of the federal policy response—as distinct from state policy responses—to aging (e.g., tax increases to fund Social Security benefits). While this is a limitation, many literatures have learned a great deal about national phenomena by using state-level variation to control for the confounding secular trends that hinder time series analyses.[1]

Our paper contributes an essential piece of evidence to the literature on the macroeconomic effects of changes in population age structures.[2] Although not focused on aging per se, most relevant to our paper are a pair of studies by Feyrer (2007, 2008) that estimate the realized effect of changes in the age distribution of workers on changes in total factor productivity using a panel of OECD and low-income countries between 1960 and 1990.[3] Feyrer concluded that the relationship between worker age and total factor productivity has an inverse-U shape; specifically, productivity growth increases with the proportion of workers ages 40-49 and decreases as the proportion who are older rises.

A contemporaneous report by the International Monetary Fund on population aging in Europe uses an empirical strategy similar to that used here. Aiyar et al. (2016) use a cross-

---

[1] For example, Shimer (2001) studied the effect of the age structure on the unemployment rate; Barro and Sala-i-Martin (1992) studied convergence across states; Finkelstein (2007) studied the aggregate effects of Medicare by using geographic variation in health insurance rates.

[2] Other studies in the growth literature have considered the importance of the "dependency ratio" without focusing on population aging specifically. Bloom, Canning, and Sevilla (2003) examine the implications of a changing age structure for economic growth in developing countries. Kögel (2005) measures the effect of changes in the *youth* dependency ratio on total factor productivity. More recently, Aksoy et al. (2015) model the effects of demographic changes on long run economic growth accounting for endogenous fertility, education and innovation.

[3] Feyrer (2008) also estimated models of changes in wage growth on changes in the age distribution of the workforce at the state and metropolitan levels using U.S. data; however the estimates were sensitive to empirical specification and generally not statistically significant.

country research design to estimate the impact of changes in the share of the labor force ages 55-64 on output, instrumenting with the 10-year lagged value of the 45-54 population share and conditioning on country fixed effects. They find evidence of large labor productivity declines as the workforce ages. In the U.S. context, a recent working paper calibrates an overlapping-generations model to study the role of changing demographics on the recent slowdown in growth (Gagnon et al., 2016). The model attributes the entire decline in real GDP growth since 1980 to population aging.

Finally, while our research addresses population aging as the large baby boom cohort exits the labor force, Shimer (2001) studied the effect of the baby boom's *entry* into the labor force on the unemployment rate using a similar method as the one employed here. Exploiting state-level variation in changes in the share of the population ages 16-24, the paper estimates the relationship between the log of the youth share and the log of the unemployment rate. To address endogenous migration, Shimer (2001) uses historical fertility rates which parallel our use of the historical age structure in a state to predict differential aging.

In the next section, we describe how population aging affects economic growth in a standard model of economic output. In Section II, we show the variation in population aging across states between 1980 and 2010. This is followed by our empirical strategy in Section III. We present our results in Section IV and conclude with a discussion of the implied magnitudes of our estimates in Section V.

I. How Population Aging Affects Economic Growth

The U.S. population has aged nearly continuously over the last century. Figure 1 shows the percent of the population aged 60 and older between 1900 and 2000, and the projected percent through 2050. The only decade in which the population did not age was the 1990s when the baby boom passed through the middle of the age distribution. The U.S. population is projected to continue aging, at a relatively faster rate through 2030 (due again to the baby boom), and at a slower rate thereafter.

The size of the U.S. population and its age distribution at any point in time are the result of historical trends in birth rates, mortality rates, and immigration rates. U.S. population aging today results from the sharp decline in the birth rate in the 1960's, which marked the end of the Baby Boom, and the long-running decline in mortality rates. Immigration can offset these demographic forces to some degree, but has not been of sufficient magnitude to reverse population aging.

But how do these demographic forces affect economic growth? Consider a general representation of aggregate economic output and its subcomponents. Let the production of a state economy be represented by the function $y_{st} = F[\Omega_{st}, k_{st}, \ell_{st}]$, where y_{st} is per capita output at time t in state s, Ω_{st} is the (per capita) stock of ideas or technology, k_{st} is an index of physical capital per person, and ℓ_{st} is the per capita effective labor input.

The effective labor input depends on the employment rate in the economy and the human capital of the workforce, and both of these components are potentially shaped by the population age structure. Among individuals, labor supply varies by age and over time. Similarly, human capital, which derives from cognition and health as well as investments in formal schooling and work experience (Mincer, 1974; Becker, 1975), varies over the individual life cycle, and across birth cohorts. Thus, we incorporate age-specific employment and human capital into the expression for the effective labor input: $\ell_{st} = p_t(a_{st})\theta_t(a_{st})$, where the function $p_t(a_{st})$ is the number of workers per person (i.e., the employment rate) at time t and depends on the older population share, represented by a_{st}. The function $\theta_t(a_{st})$ is the human capital (productivity) of the labor force and also depends on the older population share.

To illustrate how changes in these components affect output growth, we differentiate the production function and rearrange terms to express the percent change in per capita output growth in terms of production elasticities[7] and percent changes in each factor of production:

$$\frac{dy_{st}}{y_{st}} = \eta_\Omega \frac{d\Omega_{st}}{\Omega_{st}} + \eta_k \frac{dk_{st}}{k_{st}} + \eta_\ell \frac{d\ell_{st}}{\ell_{st}},$$

where $\eta_\Omega = \dfrac{\partial F(\Omega_{st}, k_{st}, \ell_{st})}{\partial \Omega_{st}} \dfrac{\Omega_{st}}{F(\Omega_{st}, k_{st}, \ell_{st})}, \eta_k = \dfrac{\partial F(\Omega_{st}, k_{st}, \ell_{st})}{\partial k_{st}} \dfrac{k_{st}}{F(\Omega_{st}, k_{st}, \ell_{st})}$, and

$$\eta_\ell = \frac{\partial F(\Omega_{st}, k_{st}, \ell_{st})}{\partial \ell_{st}} \frac{\ell_{st}}{F(\Omega_{st}, k_{st}, \ell_{st})}.$$

[7] We denote the elasticities as constant across state and time. There could be heterogeneity in these measures and our empirical analysis will explore whether these elasticities change over time. Our discussion below will also consider reasons why these elasticities may change over time.

Using the definition of ℓ, and letting the *a* superscript designate elasticities with respect to the older population share, we have:

$$\frac{dy_{st}}{y_{st}} = \eta_{\Omega}\frac{d\Omega_{st}}{\Omega_{st}} + \eta_k \frac{dk_{st}}{k_{st}} + \eta_{\ell}\left[\eta_{\theta}^{a} + \eta_{p}^{a}\right]\frac{da_{st}}{a_{st}}, \tag{1}$$

for $\eta_{\theta}^{a} = \frac{d\theta_t(a_{st})}{da_{st}}\frac{a_{st}}{\theta_t(a_{st})}$ and $\eta_{p}^{a} = \frac{dp_t(a_{st})}{da_{st}}\frac{a_{st}}{p_t(a_{st})}$.

Equation (1) shows how the relationship between output growth and growth in the older population share depends on three key elasticities. First, this relationship is a function of η_{ℓ}, the elasticity of production with respect to the economy's effective labor supply. This production elasticity with respect to labor is itself a function of the stocks of capital and technology. Second, growth in the older population share affects production growth through η_{θ}^{a}, the elasticity of labor productivity with respect to the older share. Finally, the relationship is governed by η_{p}^{a}, the elasticity of labor force participation with respect to the older share. Thus, changes in the older population share can impact the effective labor supply of the economy through two channels: by changing the fraction of the population that works and by affecting the productivity composition of the workers in the labor force. Productivity here can also include intensive margin labor supply changes as the population ages, though we will separate intensive labor supply from per-hour efficiency in our empirical analysis. The model places little structure on the relationship between the older population share and production, but we specify these particular elasticities because they are the essential components of the labor input. As noted above, the model allows the labor input to in turn affect production through interactions with the stocks of capital and technology since $\frac{\partial F(\Omega_{st}, k_{st}, \ell_{st})}{\partial \ell_{st}}$ includes these factors. Consequently, there are no assumptions here that the relationship between labor and production is independent of capital and technology.

The effects of population aging on both labor force participation and productivity are not simply mechanical functions of the age profiles in labor supply and productivity. Older workers may be complements or substitutes for younger workers such that changes in the older share may affect the economy's productivity and labor supply through interactions with younger workers. The model's human capital function makes no claims about these interactions, though we provide empirical evidence about the relationship between changes in the older share and changes in labor outcomes at younger ages.

II. Data

To construct measures of the age structure in a state, we obtain state population counts by age from the 1980, 1990, and 2000 Census Integrated Public Use Microdata Series (IPUMS) and the 2009-2011 American Community Surveys (ACS) (Ruggles et al., 2015). Due to the relatively small size of the ACS, we combine the 2009-2011 samples to construct a "2010 Census."[8] In addition to population counts, the Census and ACS contain individual-level data measuring employment status, hours worked and labor earnings in the preceding calendar year. We aggregate these data to the state-year level to obtain the state employment rate, total hours worked and total labor earnings. To facilitate sub-analyses by sector, we construct a parallel set of population and labor market measures at the level of two-digit industry, state and year. [9]

To measure aggregate output, we acquire GDP by state and year from the Bureau of Economic Analysis (BEA).[10] State GDP is defined as "the value added in production by the labor and capital located in a state," measured in dollars. These data "provide a comprehensive measure of a state's production" (BEA, 2006).[11] The state GDP data also include industry-specific output measures, which we use to study the differential impacts of aging on different sectors of the economy. Because the annual labor outcomes from the Census and ACS refer to the previous year (i.e., 1979 in the 1980 Census), we match GDP data from the year preceding the indicated Census year (i.e., 1979, 1989, 1999 or 2009).[12] However, for ease of exposition, we refer to the Census years when indexing by time below.

[8] Alternatively, we could have used state-level population statistics from the Census. However, we chose to construct our population size and labor supply measures from the same individual-level data in order to minimize differences arising from differences in data aggregation procedures. Using these noisier measures of state-level population should not affect the consistency of our estimates but may increase our standard errors.

[9] We use the 1990 Census Bureau industrial classification scheme, which is consistently reported in IPUMS for all years since 1950.

[10] Last accessed March 31, 2015.

[11] An advantage of using aggregate production instead of consumption data is that GDP includes asset income, which can be used to compensate for declines in consumption.

[12] There is still a slight misalignment between state and year for the labor outcomes since, before 2000, the Census only included information on state of residence in the current year. For 2000 and 2010 it is possible to aggregate labor outcomes by state of residence in the previous year. We conducted robustness checks of our main regressions for 2000-2010 using the aligned and misaligned measures, respectively, and found that this did not affect our results. These estimates are shown in Appendix Table A.5 and discussed below.

The BEA also collects state-level data on total employee compensation, which includes wages and salaries paid to employees as well as noncash benefits. Wages and salaries are the primary component of employee compensation and include overtime pay, sick and vacation pay, severance pay, incentive payments (e.g., commissions, tips, and bonuses), and voluntary contributions to deferred compensation plans. Noncash benefits include in-kind benefits and employer contributions to pension plans, health insurance, and social insurance programs. We use the BEA employee compensation data as a measure of *full* labor compensation in a state, and as a complement to the Census earnings data.[13]

We construct medium-run growth rates by state for all of our analysis variables. These data are presented in Table 1, where growth in a variable as of Census year *t* refers to the percent change between *t-10* and *t*. The top panel shows all Census years pooled, while the lower panels show the data decade by decade. There is significant variation across states in the size and growth rate of the 60+ population in all years. In the pooled sample, the fraction ages 60+ ranges across states and Census years from 0.095 to 0.313, with mean 0.24 and standard deviation 0.029. The 10-year growth rate of the fraction 60+ ranges from -9% to 47%, with mean 4% and standard deviation 8%. Economic growth also varies substantially across states and years. In the pooled state-year sample, the 10-year growth rate in GDP per capita ranges from -12% to 131%, with mean 55% and standard deviation 26%. Productivity growth, measured as the 10-year growth rate in GDP per worker, ranges from -8% to 117%, with mean 55% and standard deviation 19%. Finally, labor force growth, the other component of growth in GDP per capita, ranges from -10% to 9%, with mean -0.3% and standard deviation 4%.

To shed light on the regional patterns underlying the variation summarized in Table 1, we also present choropleth maps of the state variation in population aging that occurred decade by decade.[14] Between 1980 and 1990 (Figure 2A), there was relatively fast growth in the older population in the West and in the Rust Belt. At the same time, 15 states, including the large states of California, Texas, Florida, and New York, experienced a *contraction* in the relative size of their older population. Between 1990 and 2000 (Figure 2B) the majority of states experienced declines in the relative size of their older populations, with just 12 small states seeing weakly

[13] One limitation of the BEA measure of total compensation is that it does not include compensation for the self-employed. Adding in labor earnings for the self-employed using the Census and ACS has little effect on the results.
[14] Note Hawaii and Alaska are not shown in Figures 2A-2C, but are included in our analysis sample.

positive growth. However, between 2000 and 2010 (Figure 2C) the growth rate of the older population was above 15% in 20 states, including the northern Pacific and Mountain states, and nearly all of the South Atlantic states. Only 4 states—Florida, North Dakota, South Dakota, and the District of Columbia—experienced less than 5% growth during this period. Florida is notable in that by this time it *already* had a relatively high older population share.

If age-specific migration and mortality patterns were entirely independent of economic changes, then it would be useful to compare the economic outcomes of states that experienced fast population aging to states that experienced slow population aging. But economic changes can themselves shape the population age structure by affecting contemporaneous patterns of migration and mortality, and thus any association between economic growth and population aging at the state level is unlikely to represent the causal impact of population aging. As we detail in the next section, we address this issue with a research design that makes use of the fact that population age structures are to an extent the result of historical demographic patterns (e.g., fertility trends). Our research design leverages the *predetermined* components of the population age structure for identification in order to circumvent these confounding sources.

III. Empirical Strategy

To obtain an estimable specification for the differentiated production function in equation (1), we note that differentiating

$$\ln y_{st} = \eta_\Omega \ln \Omega_{st} + \eta_k \ln k_{st} + \eta_\ell [\eta_\theta^a + \eta_p^a] \ln a_{st}$$

would give equation (1). Since technology and capital at the state level are unobserved, we model their effects with state and time fixed effects. Specifically, let $\alpha_s + \gamma_t + \varepsilon_{st} = \eta_\Omega \ln \Omega_{st} + \eta_k \ln k_{st}$. This permits growth over time while also allowing states to have different levels of capital and technology. We also allow for state output shocks, modeled as ε_{st}. Our identifying assumption will be that our instrumental variable is uncorrelated with these shocks, and this assumption is discussed later. We take first-differences and include additional control variables to arrive at the following estimable specification, which is similar to specifications found in the related literature (e.g., Shimer, 2001):

$$\ln y_{s,t+1} - \ln y_{st} = \gamma_t + \beta \left[\ln\left(\frac{A_{s,t+10}}{N_{s,t+10}}\right) - \ln\left(\frac{A_{st}}{N_{st}}\right) \right] + X_{st}'\delta_t + \left(\varepsilon_{s,t+10} - \varepsilon_{st}\right), \qquad (2)$$

where y_{st} is an economic outcome (e.g., GDP per capita) for state s in Census year t, A is the number of individuals aged 60 and older, N represents the total population aged 20 and older, and X contains a set of time-varying control variables whose influence is also allowed to vary over time. We include in X the initial (period t) two-digit industry composition of the state labor force (specifically, the log of the fraction of workers in each industry) to account for initial conditions that may predispose states to particular growth paths.[15] The log-difference specification for both dependent and independent variables normalizes comparisons of growth across states with different initial population shares and yields an easily interpretable elasticity, β. When presenting our main results, we will show that our results are robust to different functional forms.

Our main outcome of interest is growth in GDP per person aged 20 and older. Thus, both the outcome and main explanatory variable are normalized by the size of the 20+ population in the state-year, which makes interpretation straightforward. Throughout the paper, we refer to variables normalized by the size of the 20+ population as "per capita" variables. To understand the mechanisms driving changes in GDP growth, we also examine specific decompositions of GDP per capita. First, we decompose GDP per capita into two components: GDP per worker (labor productivity) and the fraction of people working.[17] This decomposition enables us to assess how much of the effect of population aging on economic growth operates through changes in labor force growth as compared to changes in productivity growth.

Second, we further decompose the productivity component, GDP per worker, into three subcomponents: GDP per dollar paid to labor (i.e., GDP/earnings), earnings per hour worked (i.e., wage) and hours H per worker L (intensive labor supply). This decomposition of the productivity component tests for compensating adjustments in earnings, as opposed to changes in intensive margin labor supply. Since labor earnings may not fully reflect labor costs, we repeat the decomposition substituting BEA's measure of total labor compensation, which includes the value of in-kind benefits paid to workers. Overall, these decompositions provide a rich picture of the mechanisms driving the relationship between population aging and economic growth.

[15] In complementary work, we find that an area's initial industry structure predicts changes in labor outcomes (see Maestas, Mullen and Powell, 2013).
[17] Here too we define the number of workers as the number of workers ages 20+.

While equation (2) relates changes in state population aging to changes in state economic outcomes, changes in the age structure of a state may depend – in part – on factors related to economic growth. For example, economic decline could induce prime-aged workers to migrate out of the state while older workers may be more likely to stay given the smaller lifetime return to moving. Consequently, we would observe that aging states have less favorable economic outcomes, though this relationship is not causal.[18] Similarly, differential industry growth and decline across states may affect mortality rates and these mortality effects may not be uniform across all age groups, directly altering the age composition of states depending on their economic conditions.

To address these potential confounds, we use an instrumental variables strategy to estimate equation (2) that exploits the differential and *predictable* component of population aging across states over time. We first construct *national* census survival rates, defined as the ratio of the national population age $j+10$ in one Census to the cohort's population size in the prior Census (at age j).[19] We then multiply the number of individuals age j in the *state* in one Census by the age-specific *national* survival rate to predict the number of individuals age $j+10$ in the *state* in the next Census. For example, to predict the number of 60 year olds in Alabama in 2000, we multiply the number of 50 year olds in Alabama in 1990 by the *national* ratio of 60 year olds in 2000 to 50 year olds in 1990. This approach uses initial state composition interacted with national level cohort changes and has the advantage of disregarding variation resulting from differential state-level migration and mortality for identification. The instrument is similar in spirit to the Bartik instrument (Bartik, 1991; Blanchard and Katz, 1992), which predicts local economic growth by interacting national industry-specific growth with initial local industry composition.

More precisely, the instrument is the predicted change between t and $t+10$ in the log of the fraction of the state population 60+:

$$\ln\left(\frac{\hat{A}_{s,t+10}}{\hat{N}_{s,t+10}}\right) - \ln\left(\frac{A_{st}}{N_{st}}\right)$$

[18] There is some evidence that population aging itself may affect interstate migration; see Karahan and Rhee (2014).
[19] Note our census survival ratios incorporate international (as opposed to interstate) migration.

where $$\hat{A}_{s,t+10} = \sum_{j\geq 50} \underbrace{N_{jst}}_{\substack{\text{Total number}\\ \text{of people age}\\ j \text{ in state } s\\ \text{at time } t}} \times \underbrace{\frac{N_{j+10,t+1}}{N_{jt}}}_{\substack{\text{National growth}\\ \text{rate}\\ \text{of cohort age } j \text{ at time } t}}$$

and $$\widehat{N}_{s,t+10} = \sum_{j\geq 10} N_{jst} \times \frac{N_{j+10,t+10}}{N_{jt}}.$$

The main source of variation used by the instrument is the variation across states in the relative size of their population ages 50-59. States with a large fraction of 50-59 years olds are predicted to experience relatively large increases in the number of older individuals.[20] The variation in population aging that we exploit is predictable and observable by residents of the state before time *t*. In this manner, the instrument parallels population aging at the national level. The literature has used lags of the age structure to predict the current age structure as a way to avoid confounding by endogenous migration (Shimer, 2001; Jaimovich and Siu, 2009; Aiyar et al., 2016). Below, we provide evidence that a 10-year lag is adequate to avoid correlations with omitted variables that independently predict differential economic growth. Nonetheless, we also provide comparable estimates based on longer lags of the age structure—20, 30, and 40 years.

IV. Estimates and Mechanisms

A. Effect of Population Aging on Economic Growth

We begin with a visual depiction of our research design. In Figure 3A, each data point is an observation of the decadal change in a state, weighted by population size in the base year. The figure shows the strong negative association in the raw data between realized population aging and per capita GDP growth over the period 1980-2010. Figure 3B shows the first-stage relationship critical to our research design. Here, we see that realized population aging is strongly predicted by the predicted aging instrument. Finally, Figure 3C presents the visual reduced form relationship between the predicted aging instrument and subsequent economic growth.

Table 2 presents the coefficients summarizing these relationships after we include controls for state industry composition in the base year and time fixed effects. Panel A shows the ordinary least squares (OLS) estimates of equation (2) for the entire time period 1980-2010, and

---

[20] Some variation may also come from changes in the denominator *N*. That is, if the younger population is (predictably) growing faster in one state than in another, the first state will have less population aging by our metric *even if* the two states experienced the same (absolute or proportional) change in the number of older individuals.

separately for each decade. The dependent variable is the change in log per capita GDP. The point estimates indicate that states experiencing growth in the fraction of individuals ages 60+ also experience slower growth in per capita GDP. Using the full sample, we estimate that a 10% increase in the fraction of the state population ages 60+ is associated with a decrease in economic growth of 8.3%. Contrasting this estimate with the much larger slope coefficient in Figure 3A reveals the importance of controlling for time fixed effects. Limiting the sample to one ten-year difference at a time, we consistently find a large and statistically significant association.

As noted above, there are many reasons why state populations might age at different rates and economic growth itself could impact the state age structure by affecting migration decisions; this would bias the OLS estimate away from zero if younger workers move to faster growing places to pursue new job opportunities or, conversely, if older individuals move to slower growing places to take advantage of the lower cost of living. Similarly, if economic growth affects mortality rates, then this too may contribute bias. The direction of the bias is less obvious in this case since it depends on how any growth-induced mortality changes play out across the age distribution.

Panel B of Table 2 presents the reduced form relationship between our instrument—the predicted change in the log of the fraction of individuals 60+ in a state—and economic growth. We find that a 10% increase in the predicted fraction of the 60+ population decreases per capita GDP growth by 3.9%. Panel C shows the first-stage coefficient, conditioning on time fixed effects and controls for initial industry composition. For each 10% increase in predicted growth of the 60+ population, we find that a state actually experiences a 7.2% increase (compared to an implied 8.3% in Figure 3B). The F-statistic for the full sample is 174.24.

Main Estimates

Table 3 presents two-stage least squares estimates of the effect of population aging on economic growth for all decades pooled and separately, weighted and unweighted by base-year state population in the top and bottom rows, respectively. Using the full sample, we estimate that a 10% increase in the fraction of the population 60+ decreases economic growth by 5.5%. Our IV estimate is smaller in magnitude than the OLS estimate, consistent with systematic migration of younger individuals to faster growing areas. The difference between the OLS and IV estimates is marginally statistically significant (p=0.06).[21] The IV estimates are largely unaffected by the weighting scheme. Without weighting, we estimate a statistically significant effect of 4.8%. While noisy, the point estimates are negative for each decade, regardless of weighting. While we predict especially fast population aging in some states (e.g., Alaska), the inclusion or exclusion of these "outlier" states has little effect on our conclusions (as suggested by the similarity of the unweighted and weighted estimates in Table 3) since these states tend to be small.

Other Age Groups

While our specification models changes in per capita GDP as a function of changes in the older population share, economic growth may also be affected by changes at other points of the age distribution. Moreover, predicted increases in the 60+ population share may be correlated with predictable growth in the share of other age groups, suggesting the possibility of an omitted variable related to changes in other (correlated) age group shares. We can test for this possibility explicitly given that our instrumental variables strategy is easily extended to predict growth in other age groups. To implement this, we include multiple age groups in our specification and, as before, estimate our main model using two-stage least squares, where the instruments are the predicted changes in each included age group using the same prediction method as before. The excluded age group is the 20-29 age group. The results are presented in Appendix Table A.1. We find that only growth in the 60+ population leads to a statistically significant decrease in growth in GDP per capita. When we include all other age groups, our estimate is nearly the same as before—a 10% increase in the fraction of the population aged 60+ is associated with a 5.9% decrease in the rate of economic growth. Including or excluding the other age groups has little effect on this estimate. Consequently, we conclude that separately identifying these other age groups is not necessary for consistent estimation in our context. We provide further support for this conclusion when discussing the role of functional form restrictions next.

Functional Form Assumptions

Our main specification uses changes in the log of the older population share because it is implied by our model, and also has precedence in the literature. To test whether this log specification is driving our results, in Appendix Table A.2 we replicate Appendix Table A.1

[21] We test the equality of the estimates through a clustered bootstrap method and report how frequently the OLS estimate is smaller than the IV estimate.

using levels instead of logs and instrumenting with the corresponding predicted level changes. As before, the point estimates on the change in the older share are similar regardless of whether other age groups are also included in the model. We estimate that each percentage point increase in the older share decreases per capita GDP by over 2%. Given that the mean older population share in the sample is 0.24, a 10% increase in the older share implies a reduction in per capita GDP growth of 4.9%, which is similar to our main estimate. Appendix Table A.2 includes the implied elasticity for each model; these elasticities range between -0.54 and -0.46.

Next, we estimate our model using Poisson regression. Santos Silva and Tenreyo (2006) show that a logged dependent variable in a linear regression restricts the error term. The specification in equation (2) assumes that the error term is multiplicative in per capita GDP growth. Using an exponential specification and estimating with Poisson regression relaxes this assumption, allowing for both multiplicative and additive error terms. We replicate our main analysis using instrumental variables Poisson regression and present the results in Appendix Table A.3. We find similar results as before, further suggesting that our estimates are not driven by functional form assumptions.

Common Regional Shocks and State of Residence

In Appendix Table A.4 we show that our main estimates are robust to the inclusion of region-year interaction terms, and therefore common regional shocks are not driving our results. Appendix Table A.5 shows that the one-year misalignment in when residence is measured in the Census compared to state of residence in the previous year does not materially affect our estimates for the 2000-2010 period (the one period in which both the current and prior year's state of residence are available). The IV estimate increases in magnitude when we use the prior year's state of residence.

Mean Reversion or Confounding Trends in Output

Growth in a state's older share may be a function of the state's economic conditions, potentially confounding the causal relationship between aging and growth. OLS estimates of equation (2), as shown in Panel A of Table 2, reveal a strong negative correlation between aging and growth, even when accounting for state fixed effects (through differencing) and time fixed effects. Our instrumental variable strategy is designed to disentangle the reverse effect of growth on realized population aging from the effect of population aging on growth by using predicted changes in the state's population structure. Our IV estimates suggest that the OLS estimates are, in fact, biased away from zero, as one would expect if the older share were systematically affected by economically-induced migration patterns.

The instrumental variable strategy assumes that the initial age distribution of a state is not predictive of *trends* or mean reversion in economic output except through changes in the state age structure. The first evidence that this assumption is valid is that, if the initial age structure predicts differential economic growth, then we might expect to see statistical relationships across other age groups as well. However, as discussed above, Appendix Tables A.1 and A.2 show that only changes in the share aged 60+ are statistically related to changes in per capita GDP. It is unlikely that the initial share ages 50-59 would alone predict differential growth while variation in every other age group share would not.

Our main evidence that the identifying assumption is valid is the robustness of our estimates to use of longer lags of the age structure. In Column (1) of Appendix Table A.6, we present estimates using an instrument generated from the age distribution *20 years prior*, instead of 10 years. That is, we use the state age distribution in year *t-10* (instead of year *t*) to predict state-level population aging between *t* and *t+10*. We predict the fraction of the population ages 60+ in year *t* as well as in year *t+10* to construct the predicted change. The age distribution in year *t-10* should be disassociated with underlying economic trends between period *t* and *t+10*. The Column (1) estimate is similar to the main estimate of this paper, strongly suggesting that any pre-existing trends are uncorrelated with our instruments.

We apply the same method in Column (2) but use the age distribution from *30 years prior* to predict aging between periods *t* and *t+10*. Again, the estimate is similar. In Column (3), we use the age distribution from 40 years prior and, again, the point estimate is very similar, though the first stage weakens and the p-value is 0.102. We also show results using an instrument generated from the age structure 50 years prior, though the first stage is very weak using this instrument and we caution against interpreting the resulting estimate. We estimate a marginally significant and very large effect with this last instrument. Note that we cannot go further back since our instrument is the predicted ratio of the size of the 60+ population to the size of the 20+ population. At 60 years, we have no prediction for the size of the under-60 group. Overall, our Appendix Table A.6 results strongly suggest that our estimates are not biased by trends correlated with the initial age structure.

In Appendix Table A.7, we report estimates from a specification that controls for the initial (period *t*) log of per capita GDP in state *s* to account for trends dependent on initial economic conditions. This control is potentially important given previous evidence of convergence across states (Barro and Sala-i-Martin, 1992). Because of the biases associated with estimating a specification with a lagged dependent variable, we use the GMM estimator introduced in Arellano and Bond (1991). In Column (1), we present estimates using the Arellano-Bond estimator, using (all available) lagged values of the log of per capita GDP as instruments. The estimate is larger in magnitude than the main estimate of the paper. As a further step, in Column (2), we replicate this specification but do not use the *t-10* value of the log of per capita GDP as an instrument. The exclusion of this instrument reduces the possibility that the lagged instruments are themselves endogenous due to serial correlation in the error term. The Column (2) estimate is even larger in magnitude. Overall, the results shown in Appendix Tables A.6 and A.7 indicate that underlying trends and mean reversion are not driving our results.

B. Decomposing the Effect—Labor Force and Productivity Growth

While the literature concurs that population aging is likely to lead to slower growth in GDP per capita due to slower labor force growth, there is little evidence to suggest how population aging might affect aggregate productivity. Table 4 decomposes GDP per capita into these two components and separately estimates the effect of population aging on GDP per worker and the number of workers per capita. Column (1) reproduces the total effect of population aging on growth in GDP per capita. By construction, the estimated effects of population aging on growth in GDP per worker (Column 2) and growth in workers per capita (Column 3) sum to the total effect in Column (1).

We find that, as expected, population aging decreases labor force growth (Column 3). Specifically, a 10% increase in the fraction of the population 60+ leads to a 1.7% decrease in workers per capita. However, population aging has an even larger effect on productivity; a 10% increase in the fraction of the population 60+ leads to a 3.7% decrease in GDP per worker. Similar to our prior sensitivity test, we check whether these results are driven by not including other age groups in the specification. In Appendix Table A.8, we replicate Appendix Table A.1 using growth in the log of GDP per worker as the outcome variable. The effect of the older share is similar regardless of whether other age groups are included in the model.

To decompose the productivity effect further, we use the following identity:

$$\ln\left(\frac{GDP}{N}\right) = \ln\left(\frac{GDP}{\text{Earnings}}\right) + \ln\left(\frac{\text{Earnings}}{H}\right) + \ln\left(\frac{H}{L}\right) + \ln\left(\frac{L}{N}\right),$$

where the components are defined as:

1) $\frac{GDP}{\text{Earnings}}$ = output per dollar paid to labor
2) $\frac{\text{Earnings}}{H}$ = earnings per hour worked (wage)
3) $\frac{H}{L}$ = hours per worker (intensive margin of labor supply)
4) $\frac{L}{N}$ = fraction of population working (extensive margin of labor supply)

We then estimate equation (2) separately for the 10-year log difference of each component. The results are shown in Table 5. The estimate in the top row of column (1) indicates that growth in the older population share has little effect on the number of hours worked per worker, or intensive margin labor supply. Rather, column (2) shows that a 10% increase in the older share reduces GDP per hour worked by 3.4%. Because the intensive margin effect is small, the effect of population aging on growth in GDP per hour worked (column 2 in Table 5) is nearly the same as the effect of population aging on growth in GDP per worker (column 2 in Table 4). Thus the estimated productivity effect is not explained by reductions in the average number of hours worked.

Next, in columns (3) and (4) of Table 5 we test whether the effect of population aging on productivity growth reflects changes in the marginal product of labor. If workers are paid proportional to their marginal product of labor, then earnings should adjust in response to changes in productivity. If such adjustments are occurring, then the decline in productivity growth should be reflected in earnings per hour worked[22] and the effect of population aging on GDP per dollar earned should be zero. Our findings in columns (3) and (4) of Table 5 support these hypotheses. A 10% increase in the fraction of the population 60+ decreases growth in the average wage by a marginally statistically significant ($p<0.10$) 2% (column 4), and decreases GDP per dollar earned by a statistically insignificant 1.4% (column 3). The estimates in columns (3) and (4) sum to the estimate in column (2) by construction. Thus, the decomposition points to changes in the marginal product of labor as the primary source of the decline in productivity growth.

[22] We use total earnings divided by total hours worked in a state, which is equivalent to a weighted (by hours) average of individual hourly wages.

Since labor earnings may not fully reflect labor costs due to benefits, we repeat the decomposition substituting BEA's measure of total labor compensation for labor earnings, presented in the bottom row of Table 5. In these models, we find an even stronger negative effect of population aging on growth in the average wage when it includes monetary and in-kind benefits. Our estimates imply that a 10% increase in the fraction of the population 60+ leads to a statistically significant ($p<0.01$) 3.3% decrease in growth in average compensation per hour worked and a statistically insignificant 0.1% decrease in growth in GDP per dollar of labor compensation.

It is important to note that our productivity estimates represent the *combined effects* of all determinants of output per worker. Although output per worker can be decomposed to estimate the separate contributions of capital, labor and total factor productivity (Wong, 2001; Feyrer 2007), this approach requires data measuring the physical capital stock over time for the economic units of analysis. Unfortunately, no such government statistics on physical capital exist for U.S. states. That said, while in principle a state's physical capital stock may adjust to compensate for a smaller workforce or changes in output per worker, the fact that capital markets are integrated across U.S. states (in contrast to labor markets) means estimates from a state-based research design are unlikely to incorporate capital effects. Furthermore, because capital flows more freely than labor in response to supply and demand shocks (Kalemli-Ozcan et al., 2014; Bernard et al., 2013), any increases in the supply of capital investment due to population aging (since older individuals hold more wealth) are unlikely to accrue to the states in which they originate.

Overall, our decomposition exercise suggests that about 1/3 of the total effect of population aging on economic output growth operates through changes in labor force participation. We find little evidence that intensive margin changes are an important driver of the overall effect. The other 2/3 of the total effect is due to changes in GDP per hour worked. We show that this reduction in productivity growth is matched by a reduction in wage growth, which points to the existence of labor market adjustments that compensate for real losses in the marginal product of labor.

In the next sections, we explore potential mechanisms by which population aging leads to slower economic growth, and in particular slower growth in labor productivity. First, we estimate the effect of population aging on growth in GDP per capita at the industry level to test if the effects are concentrated in any particular industry or set of industries. Second, we examine the effects of population aging on employment and earnings for different age groups to investigate the role of spillover effects from older to younger workers.

C. Effects by Industry

It is possible that population aging affects different industries to varying degrees, depending on the age structure of their workforce, industry-specific skill demands or whether the industry produces tradable or nontradable goods or services. Venn (2008) argues that the impact of aggregate population aging should vary across industrial sector due to productivity differences. In addition, shifting consumption patterns with age may induce changes in demand for particular kinds of goods and services. For example, as people withdraw from the labor force they tend to reduce consumption of work-related goods and services and increase consumption of healthcare services (Hurd and Rohwedder, 2008; Hurst, 2008). Our state-based research design will capture these aging-induced product demand shifts to the degree that goods and services demanded by older individuals are mostly consumed in the state where they are produced. An example of such a service is health care, which in most instances must be consumed where it is produced.[23]

To explore this, we estimate equation (2) separately by industry. Although the dependent variable is based on industry-specific GDP per person in a state, population aging is measured at the state level as before. We present these industry estimates in Table 6. The first entry shows the effect of population aging on growth in output per capita of all *private* industries. This estimate is similar to our main estimate for total output per capita (private plus public sector) in column 1 of Table 4, and implies our main estimate is not driven by changes in public sector output. The rest of the entries in Table 6 show the estimated effects of population aging industry by industry. The largest effect arises in the construction industry. We estimate that a 10% increase in the fraction of the population 60+ decreases growth in construction output per capita by 8.6%. We also find a statistically significant aging-induced reduction in growth in Wholesale Trade, Retail Trade, Finance/Insurance, and Services. The estimate for Manufacturing is of similar magnitude, but imprecisely estimated. These patterns suggest that the decrease in overall economic growth cannot be explained by a reduction in the growth of one or a small number of

[23] As noted elsewhere, our research design does not capture changes in demand that drive production in other states (e.g., Internet sales) or that are dispersed uniformly across the national economy.

industries. Instead, it appears that population aging diminishes growth in most industries, with statistically inconclusive estimates for Agriculture, Mining,[24] and Transportation/Utilities.

D. Spillover Effects on Younger Age Groups

Workers in different age groups may be substitutes or complements to one another and therefore the productivity of one age group can depend on interactions with workers in other age groups. Such productivity spillovers could occur between older and younger workers if, for example, an older worker's greater experience increases not only his own productivity but also the productivity of those who work with him. In this section, we examine the effects of population aging on the employment and earnings growth of men and women in different age groups to investigate the role of spillover effects from older to younger workers.

First, we estimate equation (2) separately for men and women by ten-year age groups, where the dependent variable in each regression is the change in the log employment rate of the age-gender group. The corresponding estimates combining men and women are included in Appendix Table A.9. As before, the key independent variable in all models is the change in the log fraction of population ages 60+ (both genders combined), for which we instrument as above. The two-stage least squares estimates are shown in Table 7. We find little effect of population aging on employment growth in younger age groups, but larger reductions in employment growth in older age groups. The results suggest that an increase in the fraction of the population ages 60+ does not crowd out younger workers. Rather, these results suggest that the slowdown in employment growth induced by population aging was indeed concentrated among older individuals and, in particular, among older men. It is true, however, that as the population ages the workforce becomes older. Table 8 shows how population aging induces an increase in the *share* of the workforce that is 50 and older and a decrease in the share under 40.[25]

Table 9 presents the corresponding wage effects by age group and gender.[26] The wage estimates aggregating men and women are included in Appendix Table A.10. The outcome variable is the change in the log wage, which as before is defined as total labor earnings divided

[24] The Mining sector workforce is expected to age rapidly over the next several decades (Brandon, 2012), but because of its geographic concentration within just a few states, we lack statistical power to detect effects on economic growth.
[25] Note our results illustrate that an aging-induced reduction in the younger employment *share* does not necessarily imply an aging-induced reduction in the younger employment *rate*.
[26] In this analysis, we cannot account for the full compensation costs since the BEA does not estimate compensation data by age group.

by total hours worked (by age group, gender, state, and year). Here, we find large effects of population aging on productivity growth among younger workers, as well as older workers. Our point estimates imply that a 10% increase in the fraction of population ages 60+ reduces productivity growth across the age distribution (through age 69), and for males and females alike, by 3-5%.

Our estimates reveal how population aging-induced changes in labor supply alter the productivity composition of the workforce. We find that population aging leads to slower average wage growth for workers ages 60-69, which implies that individuals in this age range who retire tend to be *more productive* on average than those who stay in the workforce, that growth in the number of older workers drives down wages for the older age group, or both. The reduction in wage growth for younger workers could arise from the loss of positive production spillovers from retiring older workers to their younger counterparts if the productive older workers are more likely to retire.[27] More generally, lower average productivity among older workers may affect younger groups if younger and older workers are complementary inputs in production, resulting in slower wage growth for both groups.

The relative productivity of older workers relative to younger workers may depend on work experience, health, education, and a host of other factors. Disney (1996) suggested the possibility that an older workforce is a more experienced labor force with the potential for *improvements* in productivity. To this point, Feyrer (2008) notes that typical estimates of the return to experience from Mincer wage regressions imply a 60 percent difference between the productivity of 50-year old and 20-year old workers. A case study of German car manufacturers found suggestive evidence that more experienced older workers were more productive than younger workers (Börsch-Supan et al., 2008). More recently, Börsch-Supan and Weiss (2016) find no evidence of productivity declines up to age 60 at a large truck assembly plant.

Until recently, this experience-productivity advantage was in part offset by the higher educational attainment of younger workers compared to older workers. But as a result of the secular growth in educational attainment through the 1970's (Goldin and Katz, 2007), completed education among 65 year olds is rising dramatically, from 10.1 years in 1980 to an expected 13.3 years in 2020. The subsequent slowdown in educational attainment means that, in sharp contrast,

[27] Note the presence of negative wage growth effects across the age distribution is also consistent with efficiency losses arising from the "thinning" of labor markets in areas with faster population aging (Gan and Li, 2004).

completed education among 25 year olds is rising very little, from 13.3 years in 1980 to a projected 13.9 years in 2020. The net result is that the average older worker is now nearly as educated as the average younger worker.

Age-related health differences may also offset part of the experience-productivity advantage, owing to the higher prevalence of disability with age. However, trends in health suggest this too may be lessening as obesity-related disabilities disproportionately affect younger cohorts (Freedman et al., 2013). Perhaps the biggest open question pertains to the age profile of cognition and its effect on work productivity. While some aspects of cognition decline gradually over the adult lifespan (e.g., processing speed), others hold steady until late life (e.g., knowledge) (Verhaegen and Salthouse, 1997), and there is considerable heterogeneity in the timing of decline across individuals (Hartshorne and Germine, 2015). Most intriguingly, cohort improvements in cognitive functioning point to a process of cognitive aging that is itself highly plastic (Staudinger, 2015).

These age and cohort patterns in human capital acquisition and decumulation point to the possibility of heterogeneity in the effects of population aging on economic growth over time. Appendix Tables A.11-A.13 present the employment and wage effects by age and gender for each decade between 1980 and 2010. We find that the negative spillover effects on wages of younger workers were strongest in the 1980s—when employment rates among older men were at their lowest point ever, when the human capital gap between older and younger workers was closing rapidly, and prior to the proliferation of desktop computers and the Internet. [28] Since then, employment rates among older men and women have risen, and the diffusion of technology has changed the skill demands of many jobs.

While further research is needed to identify the exact mechanisms at work, our findings foretell a further slowdown in productivity growth reflecting not only compositional differences in the workforce but also real productivity losses among individuals across the age spectrum. At the same time, greater investment in human capital development throughout the lifecycle coupled with policies and practices that encourage employment at older ages could prevent these losses to some degree.

E. Reallocation of Skills

[28] We do find some weak evidence of crowd out in employment of younger workers in the 1980s.

An important advantage of our research design based on differential population aging across states is that it controls for common national shocks. As a result, extrapolating our estimates to explain or predict national trends requires additional consideration. One issue in this context is that the effects of population aging at the state level may be exacerbated or ameliorated by the systematic reallocation of skills across states. An aging population, especially one that is aging in predictable fashion, may induce highly-skilled workers to relocate to a state that is aging more slowly. This type of migration is less likely when thinking about national populating aging so its role is important to quantify.

To assess the migration response to population aging, we focus on two outcomes: (1) the fraction of individuals ages 20-59 with at least a high school degree; (2) the size of the state population. We present the estimates in Table 10. We find no relationship between changes in the older share and changes in the skill level of the 20-59 population. We present estimates using the log of the fraction with a high school degree and, separately, estimates using levels. We do not observe a statistically significant effect for the 1980-2010 period as a whole, or in any decade. The point estimates, however, are consistently positive, which suggests that, if anything, states that are aging more rapidly become slightly more productive in terms of the observed skill composition of their *potential* workforce.

In the final panel of Table 10, we estimate the effect of aging on state population size. Once again, we find no statistically significant effects for the period as a whole or for any decade, indicating that migration does not react to state-level population aging. The point estimates are positive which, if anything, is consistent with people migrating *to* states that are aging more rapidly. Overall, we find little evidence of any systematic migration resulting from population aging which could either increase or decrease the magnitude of our results.

V. Discussion and Conclusion

As the populations of developed countries become older than ever before, a persistent question has been what impact will this unprecedented demographic change have on consumption standards? Noting that population aging has been long underway in the U.S., and that changes in the population age structure of the U.S. were largely predetermined by historical trends in fertility and mortality, we use variation in the rate of population aging across U.S. states over the period 1980-2010 to estimate the economic impact of aging on state output per capita.

Over this time period and across states, we observe substantial variation in population aging, including aging rates comparable to rates forecasted for the United States in the near future.

Our estimate of the elasticity of growth with respect to aging is that a 10% increase in the fraction of the population ages 60+ decreases growth in GDP per capita by 5.5%. While we estimate this elasticity using between-state variation, by extrapolating to the national level we gain insight into the potential impact of population aging on national GDP growth. Between 1980 and 2010, the older share increased by 16.8% in the United States. Thus our estimate implies that per capita GDP growth over the same time period was 9.2% lower than it otherwise would have been absent population aging. This corresponds to a 0.3 percentage point decrease in the annual rate of growth over a time period when the average growth rate was 1.8 percentage points.

Between 2010-2020, the older share of the U.S. population is expected to rise by 21%. Thus our estimate indicates population aging will reduce per capita GDP during the current decade by 11% relative to a counterfactual in which there is no change in older share. Annualizing this rate, population aging will be responsible for a 1.2 annual percentage point decrease in per capita GDP growth, relative to the growth rate with no change in the national share 60+.[29] Between 2020-2030, the older population share will rise by 11%, implying an annual reduction in growth of 0.6 percentage points.[30] Assuming that the counterfactual growth rate is 1.88% (the growth rate between 1960 and 2010), our estimates imply that growth will slow to 0.68% this decade and 1.28% next decade.

Our estimates are larger than those predicted by the National Research Council (2012). The Council predicted a slowdown in growth in GDP per capita of 0.33-0.55 percentage points per year relative to a long-run rate of growth in GDP per capita of 1.88%. The explanation for the difference between our estimate and theirs is that the Council assumed population aging would primarily affect labor force growth and not productivity growth. Our estimate of the effect

[29] Our estimates imply that a 21% increase in the older share would decrease per capita GDP by 11.55%. Define $\tilde{g}$ as the annual growth rate that results in a 11.55% decrease in per capita GDP 10 years later; let g represent the annual growth rate in the absence of aging. Then, $(1-0.1155)y_{s,t+10} = y_{st}(1+\tilde{g})^{10}$ such that $\ln\left(\frac{(1-0.1155)y_{s,t+10}}{y_{st}}\right) = 10\ln(1+\tilde{g}) \approx 10\tilde{g}$. The implied change in the annual growth rate is given by: $10(g-\tilde{g}) = \ln(0.8845)$, or $g-\tilde{g} \approx -0.012$.

[30] Between 2030-2050, the older population share will rise by just 2%.

of population aging on labor force growth alone is similar to their estimate of the total effect of population aging.

In fact, for the 1980-2010 period, about 2/3 of the total effect of population aging on growth in GDP per capita arose from slower productivity growth, while 1/3 was due to slower labor force growth, with labor supply effects concentrated entirely among older workers. The slowdown in productivity growth applies across the age distribution and includes younger workers. We interpret this as indicating that older and younger workers are complements in production, and so the productivity of the older workforce affects the productivity of younger workers. This pattern could also arise from a loss of positive productivity spillovers from older to younger workers if productive older workers are more likely to exit the labor force. Our results are also consistent with older workers switching to less productive occupations as they transition into retirement.

While our results suggest moderate reductions in economic growth associated with population aging at the state-level, it is worth recalling that our estimates do not account for any effects at the national level that may compensate for or exacerbate the slowdown in output growth.[31] Population aging may induce broader general equilibrium effects that we cannot capture in a state-based research design, such as changes in federal tax policy. As a result, our estimates do not preclude even larger effects of population aging on per-capita economic growth in the United States in the coming decades. On the other hand, further improvements in human capital coupled with greater labor force participation at older ages could temper these effects, as well as reduce the magnitude of changes in federal tax policy that will be required to address them.

[31] The National Research Council also did not account for general equilibrium effects of population aging on the federal budget that might lead to changes in tax policy, so this is not a source of difference between our estimate and their forecast.

References

Administration on Aging (2014). "Projected Future Growth of the Older Population." U.S. Department of Health and Human Services. http://www.aoa.gov/Aging_Statistics/future_growth/future_growth.aspx (accessed on October 3, 2014).

Aiyar, Shekhar, Christian Ebeke, and Xiaobo Shao (2016). "The Impact of Workforce Aging on Euro Area Productivity." IMF Euro Area Policies, July, 4-24.

Aksoy, Yunus, Henrique S. Basso, Tobias Grasl and Ron P. Smith (2015). "Demographic Structure and Macroeconomic Trends," Manuscript, available on REPEC https://ideas.repec.org/p/bbk/bbkefp/1501.html.

Arellano, Manuel and Stephen Bond (1991). "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations." *The Review of Economic Studies*, 58(2), 277-297.

Barro, Robert J and Xavier Sala-i-Martin (1992). "Convergence." *Journal of Political Economy*, 100(2), 223-251.

Bartik, Timothy J (1991). *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Becker, G.S. (1975). "Human capital and the personal distribution of income: an analytical approach" in *Human Capital: A Theoretical and Empirical Analysis, with Special Reference to Education*, 2nd edition. New York: National Bureau of Economic Research.

Bernard, A. B., Redding, S. J., & Schott, P. K. (2013). "Testing for factor price equality with unobserved differences in factor quality or productivity." *American Economic Journal: Microeconomics*, *5*(2), 135-163.

Blanchard, Oliver Jean and Lawrence F. Katz (1992). "Regional Evolutions." *Brookings Papers on Economic Activity*, 1992(1): 1-75.

Bloom, David, David Canning, and Jaypee Sevilla (2003). *The demographic dividend: A new perspective on the economic consequences of population change*. RAND Corporation.

Börsch-Supan, Axel (2003). "Labor market effects of population aging." *Labour* 17.s1: 5-44.

Börsch-Supan, A., I. Duezguen and M. Weiss (2008). "Labor productivity in an aging society." In D. Broeders, S. Eijiffinger and A. Houben, eds. *Frontiers in Pension Finance and Reform*, Cheltenham, U.K.: Edward Elgar, pp. 83-96.

Börsch-Supan, Axel and Matthias Weiss (2016). "Productivity and age: Evidence from work teams at the assembly line." *The Journal of the Economics of Ageing*, *7*, 30-42.

Brandon, Clifford N. (2012). "Emerging Workforce Trends in the U.S. Mining Industry." Englewood, CO: Society for Mining, Metallurgy, and Exploration. https://www.smenet.org/docs/public/EmergingWorkforceTrendsinUSMiningIndustry1-3-12.pdf (accessed May 20, 2015).

Bureau of Economic Analysis (2006). "Gross Domestic Product by State Estimation Methodology." U.S. Department of Commerce. http://www.bea.gov/regional/pdf/gsp/GDPState.pdf (accessed October 1, 2014).

Burtless, Gary (2013). "The impact of population aging and delayed retirement on workforce productivity." Center for Retirement Research at Boston College Working Paper No. 2013-11.

Cutler, D. M., Poterba, J. M., Sheiner, L. M., Summers, L. H., & Akerlof, G. A. (1990). An aging society: opportunity or challenge? *Brookings Papers on Economic Activity*, 1-73.

Disney, R. (1996). *Can We Afford to Grow Older? A Perspective on the Economics of Aging*. MIT Press.

Fernald, John G. (2016). "Reassessing Longer-Run U.S. Growth: How Low?" Federal Reserve Bank of San Francisco Working Paper Series.

Feyrer, James (2007). "Demographics and productivity." *The Review of Economics and Statistics* 89, no. 1: 100-109.

Feyrer, James (2008). "Aggregate evidence on the link between age structure and productivity." *Population and Development Review*, pp. 78-99.

Finkelstein, A. (2007). "The Aggregate Effects of Health Insurance: Evidence from the Introduction of Medicare." *The Quarterly Journal of Economics*, 122(1): 1-37.

Freedman VA, Spillman BC, Andreski PM, Cornman JC, Crimmins EM, Kramarow E, Lubitz J, Martin LG, Merkin SS, Schoeni RF, Seeman TE, Waidmann TA. (2013). "Trends in late-life activity limitations in the United States: an update from five national surveys." *Demography*, 50(2): 661-671.

Gagnon, Etienne, Benjamin Kramer Johannsen, and J. David Lopez-Salido (2016). "Understanding the New Normal: The Role of Demographics." Finance and Economics Discussion Series, Division of Research & Statistics and Monetary Affairs, Federal Reserve Board, Washington D.C.

Gan, Li and Qi Li (2004). "Efficiency of Thin and Thick Labor Markets." NBER Working Paper No. 10815.

Goldin, C., and Katz, L. F. (2007). Long-Run Changes in the Wage Structure: Narrowing, Widening, Polarizing/General Discussion. *Brookings Papers on Economic Activity*, (2), 135.

Hartshorne, Joshua K. and Laura T. Germine (2015). “When Does Cognitive Functioning Peak? The Asynchronous Rise and Fall of Different Cognitive Abilities Across the Life Span.” *Psychological Science*, March 13, 2015, 1-11.

Hurd, M. D., & Rohwedder, S. (2008). “The retirement consumption puzzle: actual spending change in panel data.” National Bureau of Economic Research Working Paper #w13929.

Hurst, E. (2008). “The retirement of a consumption puzzle.” National Bureau of Economic Research Working Paper #w13789.

Jaimovich, Nir and Henry E. Siu (2009). The young, the old, and the restless: Demographics and business cycle volatility. *The American Economic Review*, *99*(3), 804-826.

Kalemli-Ozcan, S., Reshef, A., Sørensen, B. E., & Yosha, O. (2010). “Why does capital flow to rich states?” *The Review of Economics and Statistics*, *92*(4), 769-783.

Karahan, Fatih and Serena Rhee (2014). “Population Aging, Migration Spillovers, the Decline in Interstate Migration.” Federal Reserve Bank of New York Staff Report No. 699.

Kögel, Tomas (2005). "Youth dependency and total factor productivity." *Journal of Development Economics* 76, no. 1: 147-173.

Maestas, Nicole, Kathleen J. Mullen and David Powell. “The Effect of Local Labor Demand Conditions on the Labor Supply Outcomes of Older Americans.” RAND Working Paper #WR-1019, October 2013.

Mincer, Jacob A. (1974). “The Human Capital Earnings Function” in *Schooling, Experience, and Earnings*. Cambridge, MA: National Bureau of Economic Research, pp. 83-96.

National Research Council of the National Academies (2012). *Aging and the Macroeconomy: Long-Term Implications of an Older Population.* Washington, D.C.: The National Academies Press.

Ruggles, Steven, Katie Genadek, Ronald Goeken, Josiah Grover, and Matthew Sobek (2015). *Integrated Public Use Microdata Series: Version 6.0* [Machine-readable database]. Minneapolis: University of Minnesota.

Santos Silva, JMC, and Silvana Tenreyro (2006). "The log of gravity." *The Review of Economics and Statistics* 88, no. 4: 641-658.

Sheiner, L. (2014). The Determinants of the Macroeconomic Implications of Aging. *The American Economic Review*, *104*(5), 218-223.

Shimer, Robert. "The Impact of Young Workers on the Aggregate Labor Market." *Quarterly Journal of Economics* (2001), 116(3): 969-1007.

Staudinger, U. M. (2015). Images of aging: Outside and inside perspectives. *Annual Review of Gerontology & Geriatrics, 35*, 187-210.

Veen, Stephan (2008). *Demographischer Wandel, alternde Belegschaften und Betriebsproduktivität* (Vol. 18). Rainer Hampp Verlag.

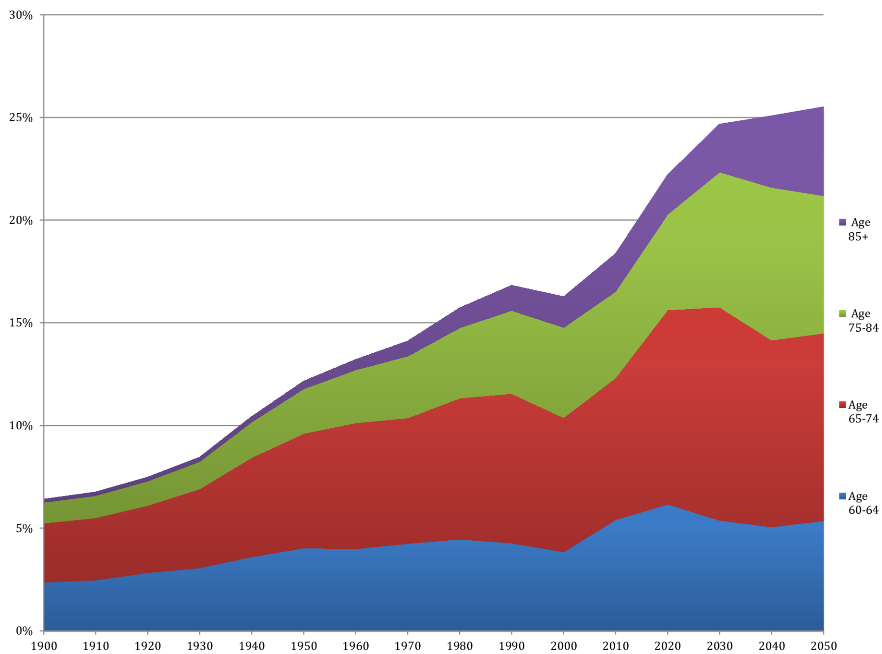
Verhaegen, P. and T.A. Salthouse (1997). "Meta-analyses of age-cognition relations in adulthood. Estimates of linear and nonlinear age effects and structural models." *Psychological Bulletin*, 122(3): 231-249.

Vogel, E., Ludwig, A., & Börsch-Supan, A. (2013). "Aging and pension reform: extending the retirement age and human capital formation" (No. w18856). National Bureau of Economic Research.

Wong, W. K. (2001). The channels of economic growth: a channel decomposition exercise. *National University of Singapore Working Paper* #0101.

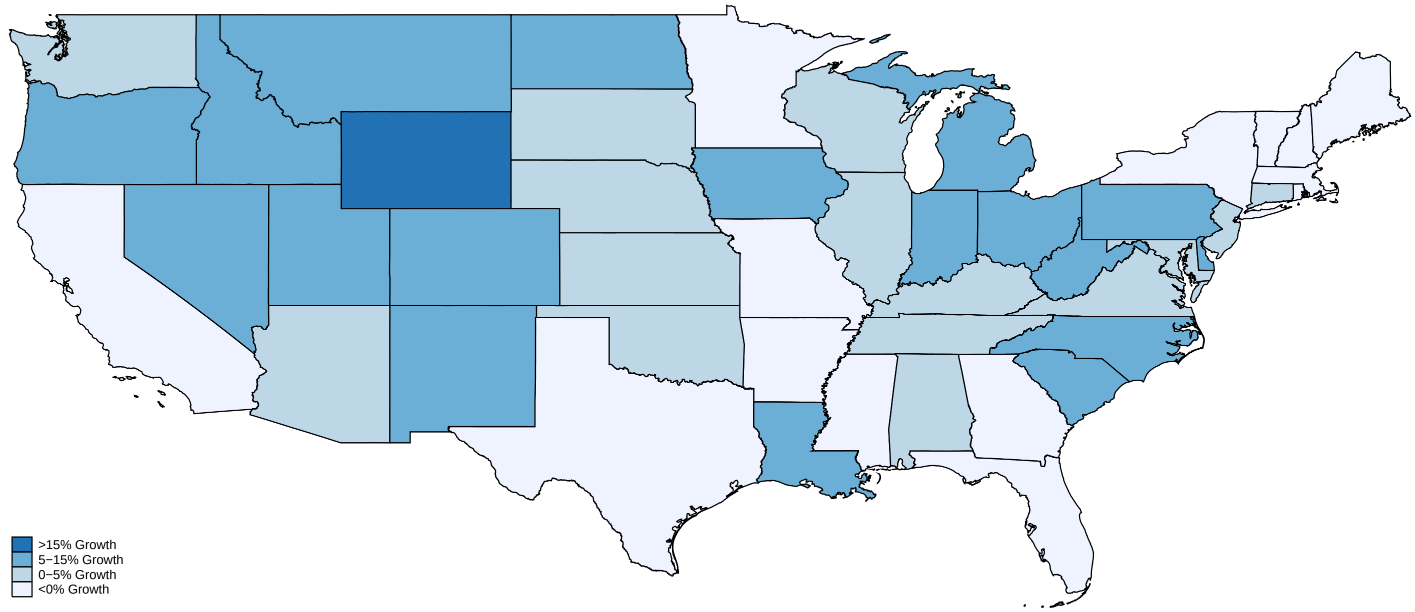
Figures

Figure 1: Percent of United States Population Age 60+: Actual and Projected – 1900-2050



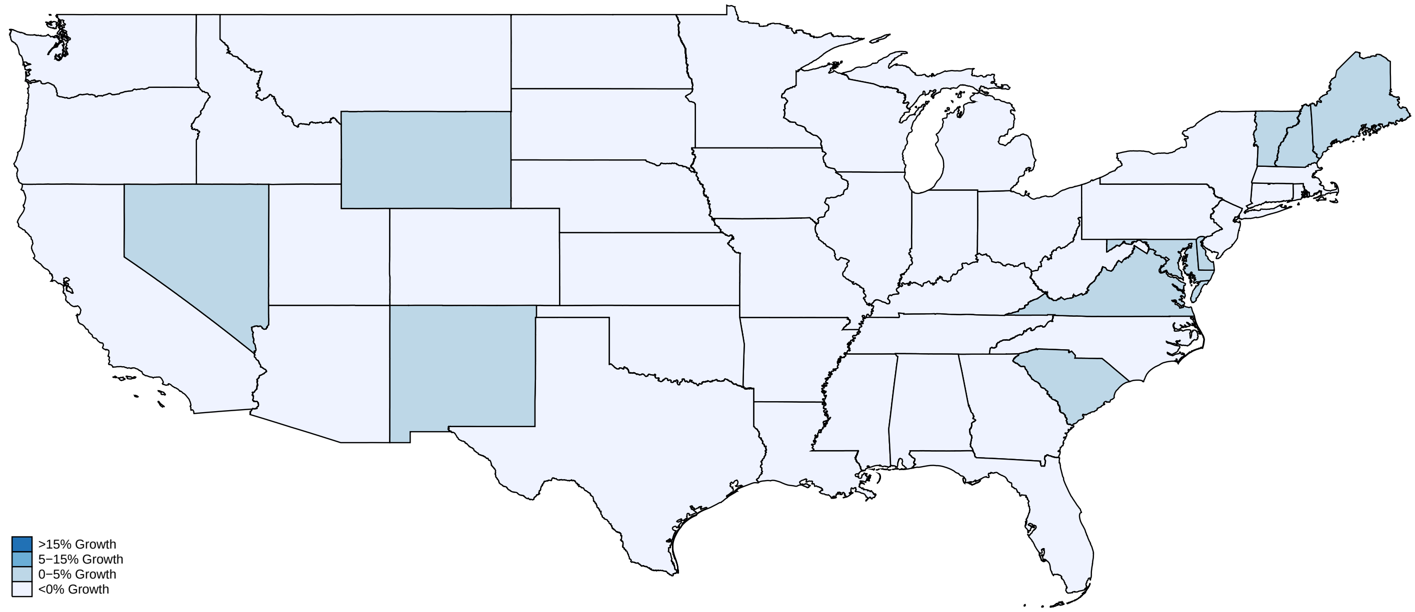
Source: U.S. Census Bureau, compiled by U.S. Administration on Aging.

Figure 2.A: Growth Rate in Age 60+ Population by State: 1980-1990



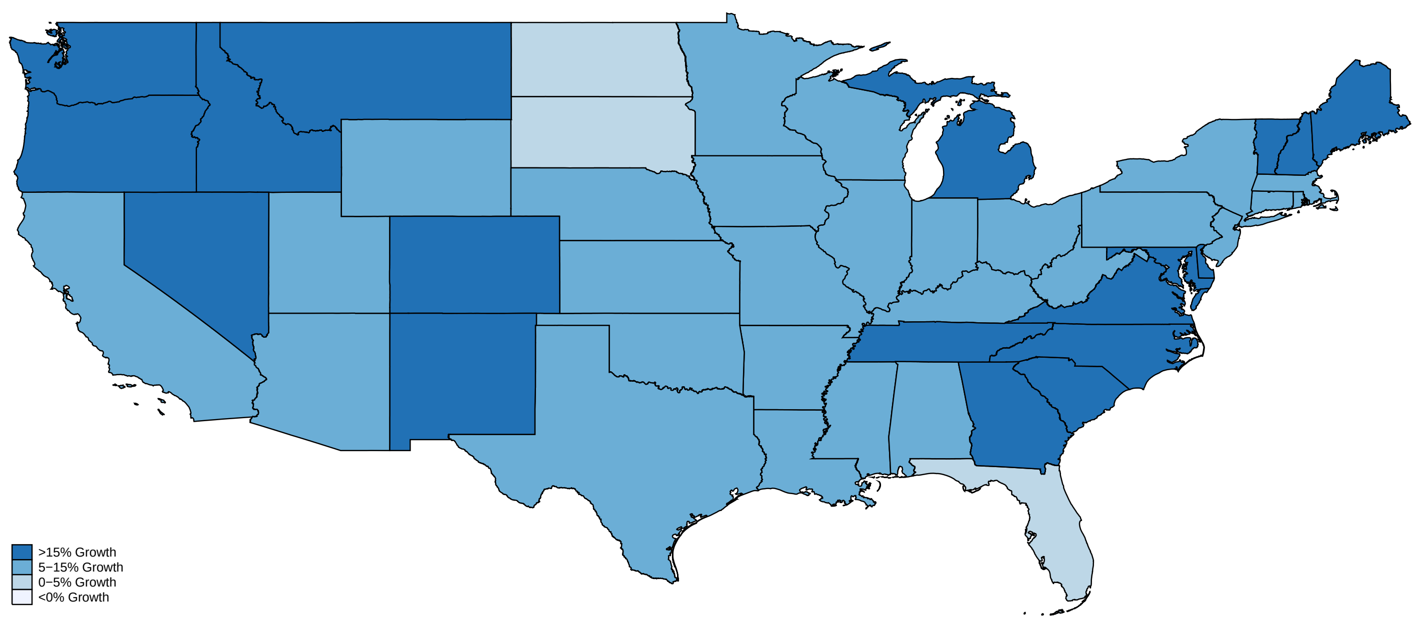
Notes: We use 1980 and 1990 Census data to construct the fraction of each state's population ages 60+. This map refers to the percentage change in this metric between 1980 and 1990.

Figure 2.B: Growth Rate in Age 60+ Population by State: 1990-2000



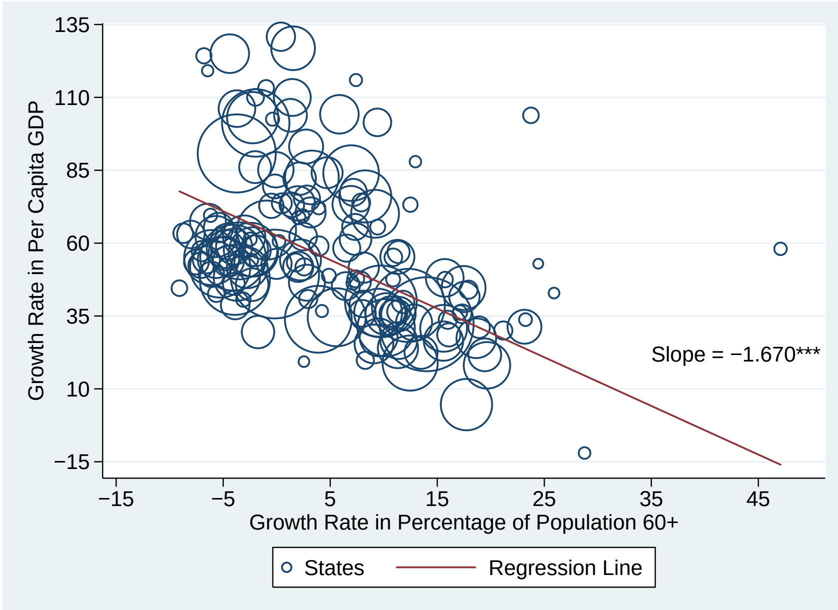
Notes: We use 1990 and 2000 Census data to construct the fraction of each state's population ages 60+. This map refers to the percentage change in this metric between 1990 and 2000.

Figure 2.C: Growth Rate in Age 60+ Population by State: 2000-2010



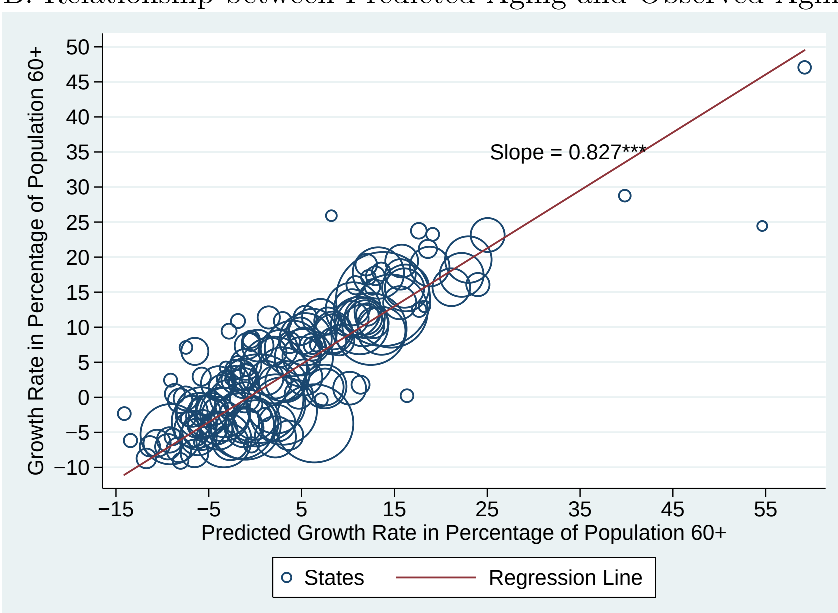
Notes: We use 2000 and 2010 Census data to construct the fraction of each state's population ages 60+. This map refers to the percentage change in this metric between 2000 and 2010.

Figure 3.A: Relationship between Aging and Per Capita GDP Growth



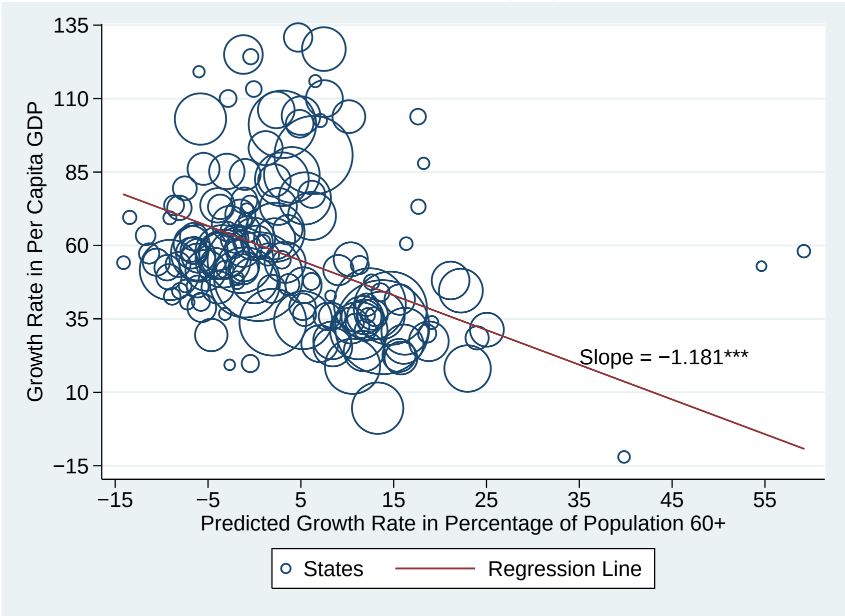
Notes: Size of bubbles reflects state population size.

Figure 3.B: Relationship between Predicted Aging and Observed Aging Growth



Notes: Size of bubbles reflects state population size.

Figure 3.C: Relationship between Predicted Aging and Per Capita GDP Growth



Notes: Size of bubbles reflects state population size.

Tables

Table 1: Summary Statistics

	Mean	Standard Dev	Min	Max
1990, 2000, 2010 (N=153)				
Fraction of Population 60+	0.240	0.029	0.095	0.313
Percent Change in Fraction of Population 60+	4.258	7.901	-9.089	47.073
Predicted Percent Change in Fraction of Population 60+	4.445	8.338	-14.103	59.196
Percent Change in GDP per Capita	55.480	25.548	-12.001	130.816
Percent Change in GDP per Worker	55.277	19.425	-8.105	117.128
Percent Change in GDP per Dollar Earned	4.343	6.259	-27.825	30.941
Percent Change in GDP per Compensation Dollar	2.090	3.631	-25.977	17.660
Percent Change in Employment-to-Population Ratio	-0.314	4.225	-10.022	9.262
1990 (N=51)				
	Mean	Standard Dev	Min	Max
Fraction of Population 60+	0.236	0.030	0.095	0.313
Percent Change in Fraction of Population 60+	2.141	4.959	-6.802	25.911
Predicted Percent Change in Fraction of Population 60+	2.307	5.078	-9.113	54.631
Percent Change in GDP per Capita	87.702	18.672	42.872	130.816
Percent Change in GDP per Worker	78.780	15.498	38.674	117.128
Percent Change in GDP per Dollar Earned	0.095	3.346	-14.269	11.216
Percent Change in GDP per Compensation Dollar	3.354	3.187	-10.264	12.604
Percent Change in Employment-to-Population Ratio	4.887	1.961	-1.709	9.262
2000 (N=51)				
	Mean	Standard Dev	Min	Max
Fraction of Population 60+	0.228	0.028	0.123	0.297
Percent Change in Fraction of Population 60+	-3.066	3.122	-9.089	28.764
Predicted Percent Change in Fraction of Population 60+	-2.836	4.321	-14.103	39.822
Percent Change in GDP per Capita	53.087	7.594	-12.001	69.543
Percent Change in GDP per Worker	53.724	7.339	-8.104	73.158
Percent Change in GDP per Dollar Earned	0.804	4.168	-27.825	14.571
Percent Change in GDP per Compensation Dollar	0.674	4.131	-25.977	17.660
Percent Change in Employment-to-Population Ratio	-0.406	1.919	-6.392	3.117
2010 (N=51)				
	Mean	Standard Dev	Min	Max
Fraction of Population 60+	0.255	0.024	0.181	0.308
Percent Change in Fraction of Population 60+	12.324	4.678	0.219	47.073
Predicted Percent Change in Fraction of Population 60+	12.487	5.749	-1.898	59.196
Percent Change in GDP per Capita	32.955	9.985	4.599	87.947
Percent Change in GDP per Worker	38.677	8.133	16.249	87.025
Percent Change in GDP per Dollar Earned	10.706	3.810	3.366	30.941
Percent Change in GDP per Compensation Dollar	2.370	3.068	-7.499	17.042
Percent Change in Employment-to-Population Ratio	-4.208	2.259	-10.022	1.806

Notes: Unit of observation is state-year. There are 51 observations per year and 153 total. All percent changes refer to ten year changes: $\frac{X_t - X_{t-10}}{X_{t-10}}$. "GDP per Dollar Earned" refers to GDP divided by total labor earnings. "GDP per Compensation Dollar" refers to GDP divided by total compensation to employee (wages and in-kind benefits). All percentage changes are defined in real terms.

Table 2: Results

Panel A:	**Ordinary Least Squares Estimates**			
Dependent Variable:	$\Delta \ln$ (GDP / N)			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{A}{N})$	-0.826***	-0.853***	-1.344***	-0.608***
	(0.140)	(0.220)	(0.332)	(0.208)
No. Obs.	153	51	51	51

Panel B:	**Reduced Form Estimates**			
Dependent Variable:	$\Delta \ln$ (GDP / N)			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{\hat{A}}{\hat{N}})$	-0.390***	-0.563**	-0.375	-0.306**
	(0.134)	(0.215)	(0.429)	(0.172)
No. Obs.	153	51	51	51

Panel C:	**First Stage Estimates**			
Dependent Variable:	$\Delta \ln$ (A / N)			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{\hat{A}}{\hat{N}})$	0.716***	0.627***	0.504***	0.865***
	(0.054)	(0.119)	(0.161)	(0.071)
No. Obs.	153	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 3: Instrumental Variable Estimates: Effect of Aging on GDP Growth

Dependent Variable:	$\Delta \ln$ (GDP / N)			
	Weighted by Population			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{A}{N})$	-0.545***	-0.898**	-0.744	-0.354**
	(0.173)	(0.336)	(0.655)	(0.194)
No. Obs.	153	51	51	51
	Unweighted			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{A}{N})$	-0.478***	-0.361	-0.996***	-0.258**
	(0.161)	(0.319)	(0.369)	(0.152)
No. Obs.	153	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 4: Decomposing Main Effect

	(1)	(2)	(3)
Dependent Variable:	Δ ln(GDP / N)	Δln(GDP / L)	Δln(L / N)
$\Delta \ln(\frac{A}{N})$	-0.545***	-0.373**	-0.172***
	(0.173)	(0.161)	(0.047)
No. Obs.	153	153	153

Notation: L = number of workers

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. The coefficients presented in Columns (2) and (3) mechanically sum to the main effect presented in Column (1). Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 5: Decomposing the Productivity Effect

	Decomposing Δln(GDP/L)		Decomposing Δln(GDP/H)	
	(1)	(2)	(3)	(4)
Dependent Variable:	Δln(H/L)	Δln(GDP/H)	Δln(GDP/Earnings)	Δln(Earnings/H)
$\Delta\ln(\frac{A}{N})$	-0.031	-0.343**	-0.145	-0.197*
	(0.033)	(0.151)	(0.112)	(0.113)
No. Obs.	153	153	153	153
	(1)	(2)	(3')	(4')
Dependent Variable:	Δln(H/L)	Δln(GDP/H)	Δln(GDP/Compensation)	Δln(Compensation/H)
$\Delta\ln(\frac{A}{N})$	-0.031	-0.343**	-0.011	-0.331***
	(0.033)	(0.151)	(0.108)	(0.123)
No. Obs.	153	153	153	153

Notation: L = number of workers; H = total number of hours worked; Earnings = total labor earnings; Compensation = total compensation paid to workers.

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. The coefficients in Columns (3) and (4) mechanically add up to the effect estimated in Column (2). The coefficients in Columns (1) and (2) mechanically add up to the effect estimated in Column (2) of Table 4. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 6: Effect of Aging on Industry-Specific GDP

	Private Industries	Agriculture	Mining	Construction	Manufacturing	Transportation / Utilities
$\Delta\ln(\frac{A}{N})$	-0.590***	0.170	0.873	-0.860**	-0.361	-0.270
	(0.201)	(0.853)	(1.919)	(0.399)	(0.486)	(0.389)
	Wholesale Trade	Retail Trade	Finance / Insurance	Services	Public Admin	
$\Delta\ln(\frac{A}{N})$	-0.472**	-0.397**	-0.624**	-0.471**	-0.341**	
	(0.218)	(0.207)	(0.277)	(0.221)	(0.184)	

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. The outcome is the log of industry-specific GDP per person in the state. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 7: Age-Specific Labor Outcomes: Change in Log of Employment Rate

				Men			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.003	-0.014	0.015	-0.082*	-0.313***	-0.447**	-0.762***
	(0.045)	(0.027)	(0.022)	(0.043)	(0.117)	(0.200)	(0.278)
No. Obs.	153	153	153	153	153	153	153
				Women			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	0.018	-0.071	-0.026	-0.037	-0.241*	-0.132	-0.702*
	(0.050)	(0.045)	(0.050)	(0.059)	(0.124)	(0.269)	(0.411)
No. Obs.	153	153	153	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 8: Age-Specific Labor Outcomes: Change in Log of Employment Share

				Men			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.243***	-0.300***	0.096	0.399***	0.769***	0.728***	0.226
	(0.083)	(0.087)	(0.087)	(0.082)	(0.116)	(0.162)	(0.358)
No. Obs.	153	153	153	153	153	153	153
				Women			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.215***	-0.264***	0.176*	0.583***	1.097***	0.946***	0.133
	(0.080)	(0.096)	(0.100)	(0.085)	(0.112)	(0.271)	(0.493)
No. Obs.	153	153	153	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 9: Age-Specific Labor Outcomes: Change in Log of Wage

				Men			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.422***	-0.325***	-0.402***	-0.477***	-0.498***	0.129	0.429
	(0.150)	(0.119)	(0.113)	(0.096)	(0.107)	(0.261)	(0.507)
No. Obs.	153	153	153	153	153	153	153
				Women			
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.342**	-0.404***	-0.376***	-0.433***	-0.324**	0.045	0.712
	(0.135)	(0.137)	(0.123)	(0.123)	(0.125)	(0.276)	(0.641)
No. Obs.	153	153	153	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table 10: Testing for Reallocation of Skills

Dependent Variable:	$\Delta\ln$(Fraction 20-59 with HS Degree)			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta\ln(\frac{A}{N})$	0.092	0.217	0.056	0.054
	(0.148)	(0.184)	(0.337)	(0.127)
No. Obs.	153	51	51	51
Dependent Variable:	Δ(Fraction 20-59 with HS Degree)			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta\ln(\frac{A}{N})$	0.105	0.258	0.058	0.059
	(0.168)	(0.219)	(0.382)	(0.143)
No. Obs.	153	51	51	51
Dependent Variable:	$\Delta\ln$(Population)			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta\ln(\frac{A}{N})$	0.150	0.353	0.382	0.007
	(0.194)	(0.414)	(0.867)	(0.133)
No. Obs.	153	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Appendix

Table A.1: Effects of Other Age Groups

Dependent Variable:	$\Delta \ln$ (GDP / N)			
Δ ln(Ages 30-39 / N)	-0.112			
	(0.192)			
Δ ln(Ages 40-49 / N)	-0.279	-0.261		
	(0.226)	(0.218)		
Δ ln(Ages 50-59 / N)	-0.104	-0.051	-0.063	
	(0.228)	(0.200)	(0.198)	
Δ ln(Ages 60+ / N)	-0.594***	-0.550***	-0.527***	-0.545***
	(0.191)	(0.153)	(0.164)	(0.173)
No. Obs.	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.2: Effects of Other Age Groups Using Levels

Dependent Variable:	$\Delta \ln$ (GDP / N)			
Δ (Ages 30-39 / N)	-0.539			
	(0.939)			
Δ (Ages 40-49 / N)	-1.576	-1.450		
	(1.197)	(1.177)		
Δ (Ages 50-59 / N)	-0.848	-0.462	-0.543	
	(1.615)	(1.399)	(1.391)	
Δ (Ages 60+ / N)	-2.252**	-2.019***	-1.901**	-2.030**
	(0.894)	(0.748)	(0.795)	(0.828)
Implied Elasticity	-0.540	-0.485	-0.456	-0.487
No. Obs.	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year. "Implied Elasticity" relates to the estimate for the 60+ population and is calculated by evaluating at the sample mean for 60+ population share.

Table A.3: Instrumental Variable Poisson Estimates: Effect of Aging on GDP Growth

Dependent Variable:	GDP / N			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{A}{N})$	-0.509***	-0.924***	-0.962**	-0.337**
	(0.129)	(0.283)	(0.453)	(0.136)
No. Obs.	153	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Period t GDP per capita is included as an offset (the coefficient is constrained to equal 1). Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.4: IV Estimates with Region-Year Interactions: Effect of Aging on GDP Growth

Dependent Variable:	$\Delta \ln$(GDP / N)			
	1980-2010	1980-1990	1990-2000	2000-2010
$\Delta \ln(\frac{A}{N})$	-0.585**	-0.690	-0.895	-0.447**
	(0.250)	(0.463)	(0.668)	(0.235)
No. Obs.	153	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies interacted with Census regions; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.5: Using Previous Year's State of Residence: 2000-2010

	OLS	Reduced Form	First Stage	IV
$\Delta \ln(\frac{A}{N})$	-0.634***	-0.348**	0.878***	-0.396**
	(0.204)	(0.174)	(0.070)	(0.192)
No. Obs.	51	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies interacted with Census regions; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year. For this table, $\Delta \ln(\frac{A}{N})$ (and the corresponding instrument) are generated using each individual's prior year state of residence. This information is first available in the 2000 Census.

Table A.6: Lagged Instruments

Dependent Variable:	$\Delta \ln$(GDP / N)			
	(1)	(2)	(3)	(4)
$\Delta \ln(\frac{A}{N})$	-0.503***	-0.450**	-0.543	-2.264*
	(0.184)	(0.214)	(0.325)	(1.130)
Instrument Lag	20 Year	30 Year	40 Year	50 Year
First Stage F-Stat	103.47	85.07	13.02	3.05
No. Obs.	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Other variables included: year dummies and "Industry Lags" when noted. These are the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year. The main results of this paper use a 10 year instrument lag – using period t data to predict the period $t+10$ age structure. Column (1) uses an instrument generated using Census population data from year $t-10$; Column (2) generates the instrument from year $t-20$; Column (3) generates the instrument from year $t-30$; Column (4) generates the instrument from year $t-40$.

Table A.7: Controlling for Initial Per Capita GDP

Dependent Variable:	$\Delta \ln(GDP/N)_{t+10}$	
	(1)	(2)
$\Delta \ln(\frac{A}{N})$	-0.603***	-0.778***
	(0.138)	(0.194)
Instruments for $\Delta \ln(GDP/N)_t$	10+ years	20+ years
No. Obs.	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year. We also control for $\Delta \ln(GDP/N)_t$ and consider this variable endogenous. In Column (1), we include lagged levels of the log of per capita GDP for years $t-10$ and earlier as instruments. In Column (2), we use lagged levels of the log of per capita GDP for years $t-20$ and earlier as instruments

Table A.8: Productivity Effects for Other Age Groups

Dependent Variable:	$\Delta \ln$ (GDP / L)			
Δ ln(Ages 30-39 / N)	0.020			
	(0.190)			
Δ ln(Ages 40-49 / N)	-0.153	-0.157		
	(0.212)	(0.207)		
Δ ln(Ages 50-59 / N)	-0.039	-0.048	-0.055	
	(0.219)	(0.190)	(0.190)	
Δ ln(Ages 60+ / N)	-0.363**	-0.371**	-0.357**	-0.373**
	(0.181)	(0.147)	(0.153)	(0.161)
No. Obs.	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.9: Age-Specific Labor Outcomes: Change in Log of Employment Rate

	Men and Women						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	0.006	-0.044	-0.014	-0.082*	-0.318***	-0.307	-0.723***
	(0.042)	(0.028)	(0.028)	(0.042)	(0.105)	(0.199)	(0.266)
No. Obs.	153	153	153	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.10: Age-Specific Labor Outcomes: Change in Log of Wage

	Men and Women						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.405***	-0.360***	-0.407***	-0.482***	-0.476***	0.076	0.444
	(0.146)	(0.127)	(0.114)	(0.102)	(0.096)	(0.227)	(0.458)
No. Obs.	153	153	153	153	153	153	153

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.11: Employment and Wages, 1980-1990

	Δln(Employment Rate), Men						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.129	-0.104*	-0.122***	-0.483***	-1.084***	-1.534***	-2.497***
	(0.087)	(0.059)	(0.040)	(0.108)	(0.262)	(0.376)	(0.924)
No. Obs.	51	51	51	51	51	51	51

	Δln(Employment Rate), Women						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.102	-0.201	-0.065	-0.146	-0.606**	-0.555	-2.365*
	(0.114)	(0.126)	(0.137)	(0.189)	(0.282)	(0.685)	(1.216)
No. Obs.	51	51	51	51	51	51	51

	Δln(Wage), Men						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-1.335***	-0.906***	-1.170***	-0.889***	-1.206***	0.432	1.831
	(0.451)	(0.252)	(0.276)	(0.256)	(0.423)	(0.685)	(1.515)
No. Obs.	51	51	51	51	51	51	51

	Δln(Wage), Women						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-1.118***	-1.205***	-1.047***	-1.000***	-1.159**	-0.326	0.722
	(0.388)	(0.324)	(0.274)	(0.342)	(0.466)	(0.654)	(1.291)
No. Obs.	51	51	51	51	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.12: Employment and Wages, 1990-2000

	Δln(Employment Rate), Men						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta\ln(\frac{A}{N})$	0.066	0.059	0.075	0.172	0.157	0.452	2.550**
	(0.090)	(0.062)	(0.078)	(0.107)	(0.255)	(0.471)	(1.284)
No. Obs.	51	51	51	51	51	51	51

	Δln(Employment Rate), Women						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta\ln(\frac{A}{N})$	-0.032	-0.032	-0.081	-0.043	-0.582*	0.155	0.62
	(0.146)	(0.132)	(0.116)	(0.179)	(0.299)	(0.513)	(0.979)
No. Obs.	51	51	51	51	51	51	51

	Δln(Wage), Men						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta\ln(\frac{A}{N})$	0.124	-0.170	-0.115	-0.681**	0.072	0.262	2.755
	(0.306)	(0.249)	(0.269)	(0.269)	(0.366)	(0.692)	(2.176)
No. Obs.	51	51	51	51	51	51	51

	Δln(Wage), Women						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta\ln(\frac{A}{N})$	0.036	-0.185	-0.349	-0.254	0.268	-0.054	-2.276
	(0.267)	(0.307)	(0.225)	(0.301)	(0.385)	(0.759)	(2.155)
No. Obs.	51	51	51	51	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.

Table A.13: Employment and Wages, 2000-2010

	Δln(Employment Rate), Men						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	0.031	0.002	0.056**	0.012	-0.126	-0.270	-1.167***
	(0.068)	(0.043)	(0.028)	(0.043)	(0.133)	(0.264)	(0.341)
No. Obs.	51	51	51	51	51	51	51

	Δln(Employment Rate), Women						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	0.093	-0.024	0.013	0.016	0.054	-0.040	-0.411
	(0.079)	(0.038)	(0.027)	(0.044)	(0.154)	(0.320)	(0.545)
No. Obs.	51	51	51	51	51	51	51

	Δln(Wage), Men						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.198*	-0.112	-0.150	-0.210**	-0.378***	-0.062	-1.075
	(0.114)	(0.120)	(0.120)	(0.100)	(0.137)	(0.318)	(1.040)
No. Obs.	51	51	51	51	51	51	51

	Δln(Wage), Women						
Ages	20-29	30-39	40-49	50-59	60-69	70-79	80-89
$\Delta \ln(\frac{A}{N})$	-0.120	-0.112	-0.073	-0.235**	-0.152	0.255	1.801
	(0.111)	(0.113)	(0.105)	(0.119)	(0.154)	(0.329)	(1.500)
No. Obs.	51	51	51	51	51	51	51

Notes: Significance Levels: *10%, **5%, ***1%. Standard errors in parentheses adjusted for clustering at state level. Each observation is weighted by period t population. Other variables included: year dummies; the log of the fraction of workers in period t working in each of the following industries: agriculture, mining, construction, manufacturing, transportation, communications / utilities, wholesale trade, retail trade, finance / insurance / real estate, business and repair services, personal services, recreation services, professional services, and public administration. The effects of these industry composition variables are allowed to vary by year.